Evaluation of Potato Late Blight Forecasts Modified to Include Weather Forecasts: A Simulation Analysis

R. Raposo, D. S. Wilks, and W. E. Fry

First and third authors, Department of Plant Pathology; second author, Department of Soil, Crop and Atmospheric Sciences, Cornell University, Ithaca, NY 14853.

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ABSTRACT

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The potential effect of incorporating weather forecasts into potato late blight disease forecasts for timing protectant fungicide applications was investigated. Fungicide applications, fungicide weathering, and pathogen development were simulated with a system of field-tested computer simulation models, using 50 yr of weather data from Steuben County, New York. Weather forecasts were simulated with a probability model that relates distributions of observed high relative humidity periods and mean temperature to forecasts produced by the National Meteorological Center. Simulated weather forecasts (with accuracy equivalent to those of real forecasts) improved the efficiency in the use of fungicide scheduled with BLITECAST: The area under the disease progress curve (AUDPC) was decreased by about 5%, but the same number of fungicide sprays was used. The maximum contribution of a weather forecast was determined by using perfect knowledge of future weather 1 and 2 days in advance as the weather forecast. Such perfect knowledge of future weather used with BLITECAST or with a simulation-based disease forecast decreased AUDPC by about 8 or 10%, respectively. Finally, two additional sets of simulations were done with weather data modified to be less favorable to late blight. In these simulations, weather forecasts provided an increasing benefit as conditions for late blight development became less favorable.

Disease forecasts are a useful component in plant disease management. They enable predictions of disease outbreaks, and therefore lead to improved use of control measures. A large amount of research has been directed at forecasting potato late blight, caused by *Phytophthora infestans* (Mont.) de Bary. Three attributes of late blight that justify the use of forecasting (2) are its potential for severe damage (18) through tuber infections or defoliation; its strong dependence on weather conditions (2,27), which make late blight occurrence irregular, and sometimes explosive; and availability of management practices for disease suppression. Independent of forecasts, the current recommended practices in the northeastern United States are to apply a protectant fungicide every week, starting when plants are about 15–20 cm high (17).

The basis for the development of late blight forecasts in Europe and the United States has been analysis of historical weather data relative to epidemic records (1,8,16,20,24,31). These disease forecasts determine the environmental conditions needed for the initial appearance of late blight and, therefore, indicate when fungicide applications should be initiated. The most broadly used forecast system in the United States is BLITECAST (23), which combines and partly modifies the two older forecasts of Hyre (22) and Wallin (31). BLITECAST has two components: One predicts the first occurrence of late blight, and the other establishes a fungicide spray schedule according to the weather conditions accumulated in the previous 7-day period. Alternatively, a simulation forecast derived from analysis of a late blight development simulation model (13) schedules spray applications during the season but does not attempt to predict the initial appearance. Unlike BLITECAST, this system recommends fewer sprays for resistant cultivars, and the timing is based on weather conditions, as well as fungicide weathering.

These two disease forecast systems are based on identifying weather favorable for secondary cycles of pathogenesis (12). The most important factor for disease development is the potential for a high reproductive rate of the pathogen (12), and, thus, environmental conditions conducive to inoculum production and infection are the basis for these two disease forecast procedures. The implicit assumption is that inoculum is present each year and able to initiate an epidemic (21,22). This makes forecast system evaluation under field conditions difficult to interpret (11,22) because inoculum availability and forecast performance are confounded.

BLITECAST has contributed to the elimination of unnecessary fungicide applications at the beginning of the season, but it does not provide consistent benefit for timing the frequency of fungicide applications (10,11,14). Evaluation of BLITECAST by computer simulation or in field experiments did not show a better efficiency of fungicide use when compared to weekly applications (11). The simulation-based forecast recommended less fungicide for resistant than for susceptible cultivars but recommended the same frequency to susceptible cultivars as did BLITECAST (13).

It has been suggested that the failure of BLITECAST to schedule fungicide applications more effectively than the conventional weekly schedule is due to the use of past weather rather than past and future weather. BLITECAST recommends sprays after weather conditions have been conducive to disease development, when applications of protectant fungicide are not effective against the established infections (23).

Few attempts have been made to incorporate weather forecasts into disease forecasts. This approach may represent a major opportunity to improve disease management. One of the most successful initial attempts has been the use of National Weather Service precipitation probabilities to predict infection periods of *Botrytis squamosa* on onion (29,30). The lack of predictions for parameters important to disease development (especially duration of moist periods) may have been the main factor preventing previous use of weather forecasts in disease forecasts. However, a model developed by Wilks and Shen (32) has recently become available and predicts probability distributions throughout high relative humidity periods and mean temperatures during those moist periods. It is based on forecasts issued by the National Meteorological Center (32). The Wilks and Shen model enables the evaluation of the potential benefit of incorporating weather forecast variables into disease forecasts (32). The Wilks and Shen model was constructed using the three-hourly forecasts of temperature and dewpoint given in the FOUS 12 guidance (7). (FOUS 12 is a compilation of forecasts produced and issued by the National Meteorological Center. It provides a series of forecasts including the three-hourly forecasts for temperature and dewpoint.) Forecasts of high relative humidity duration and associated mean temperatures were derived using a specific technique, termed model output statistics (MOS) (15). The Wilks and Shen model (32) describes the statistical relationship between MOS-derived forecasts (predicted weather) and the actual (observed) weather. According to the Wilks and Shen model (32), the probability of a specific number of hours of relative humidity above or below a threshold of interest, given a particular MOS forecast for relative humidity duration, is described by a beta distribution. Parameters of the distribution depend on the MOS forecast. Differences between MOS forecast and observed average temperatures during this period are normally distributed. The relationships (between MOS-derived forecasts and observed weather) described by the Wilks and Shen model (32) are reasonably accurate for 23 h into the future.

The availability of mechanistic simulation models of the potato late blight pathosystem (4–6) in combination with the recently available weather forecasts and probablistic models, enable simulation analysis of the contribution of weather forecasts to late blight forecasts. The late blight models describe pathogen development, fungicide dynamics and effect as a function of weather, and cultivar resistance (4–6). The disease models were developed and validated in small field plots (4–6). Previous tests of predictions from the late blight models have demonstrated their considerable accuracy in predicting effects of various treatments (4,9,25,26,28). Thus, the models should be good predictors of results from small field plots, and are appropriately used when the need for tremendous numbers of applications over a wide variety of environmental conditions mean that field experiments are prohibitively expensive and time consuming.

This research had two goals. The first was to estimate via simulation analysis the potential improvement in disease forecasts that is possible when weather forecasts (which are subject to error, as opposed to perfect knowledge) are incorporated into BLITECAST to time applications with protectant fungicide. Criteria for determining improvements were the degree of disease suppression and numbers of fungicide applications. The second goal was to estimate the maximum potential contribution of weather forecasts to enhance the efficacy of disease forecasts. All experiments were done using computer simulation analyses. For the first goal, we used the model of Wilks and Shen to incorporate simulated weather forecasts consistent in quality with real forecasts. For the second goal, we assumed perfect knowledge of future weather 1 and 2 days in advance.

MATERIALS AND METHODS

Simulation experiments. A model that simulates potato late blight development as a function of the environment and cultivar resistance (4) was combined with a model of chlorothalonil fungicide deposition and weathering (5,6). This will be referred to as the "combined model." The common parameters used in all simulation runs were: length of the season (from median emergence [early June] until vine kill) was 85 days; the late blight epidemic was initiated on day 24 after emergence with one lesion per 10 plants; a susceptible cultivar was used; and protectant fungicide (chlorothalonil) was applied at the rate of 1.34 kg a.i./ha.

Simulations were done with a weather data set consisting of 50 growing seasons from National Oceanic and Atmospheric Administration (NOAA) weather records for Steuben County, NY. The combined model was driven by daily rainfall, mean daily temperature, hours of relative humidity ≥90%, and mean temperature during this high humidity period. The start and end of a 24-h period for the model was from noon on one day to noon on the next. The original 50-yr data set was considered favorable because late blight has occurred frequently in this region during those 50 yr. Two additional weather data sets were constructed that on average were less favorable to late blight. The first of these was termed moderately favorable and was constructed from the original set by subtracting 2 h from each high relative humidity period. The second set was termed unfavorable and was constructed from the original by subtracting 4 h from each period of high relative humidity. Schedules for fungicide applications in the simulations were determined according to BLITECAST (23) and a simulation-based forecast (13). The resulting recommendations were incorporated into the combined model and the effects of these schedules were then simulated in the combined late blight model. When using observed (previous) weather, a spray was simulated the day after the appropriate disease forecast threshold had been exceeded. Both disease forecast systems were updated after each 24-h period. The initial spray was always applied on day 26 after median emergence.

Incorporation of weather forecasts into BLITECAST. Weather forecasts were incorporated into BLITECAST via severity values, one of the two components of BLITECAST. Severity values determine how favorable the daily weather is for late blight development (22). This concept was developed by Wallin (31); severity values can equal 0, 1, 2, 3, or 4 and are based on relative humidity duration and average temperature during the high relative humidity period. Different ranges of temperature and relative humidity duration define each severity value (SV). For example, an SV equal to one is obtained when a day has recorded a number of hours of relative humidity (RH) ≥90% between 16 and 18, and an average temperature during this period between 7.2 and 11.6 C, or 13–15 h of RH ≥90% with 11.7–15.0 C, or 10–12 h of RH ≥90% with 15.1–26.6 C.

The Wilks and Shen model (32) was used to calculate the probability for each severity value for the succeeding 23 h, given a particular weather forecast, and, assuming that temperature forecast errors (not the temperatures themselves) are independent of humidity duration forecasts. The following equation was used:

$$P(\mathrm{SV}=x)=\sum_i P(T_{x,\mathrm{l}_i}\leq T\leq T_{x,\mathrm{u}_i})P(y_{x,\mathrm{l}_i}\leq y\leq y_{x,\mathrm{u}_i}),\quad x=1,2,3,4;\quad i=1,2,3 \tag{1}$$

where $P(.)$ denotes probability; y is the duration (hours) of relative humidity ≥90% that will be observed in the next 23 h, given a particular forecast, and its probability is computed from a beta distribution with parameter values that depend on the MOS forecast; T is the temperature (C) that will be observed, and its probability is calculated using the distribution of temperature forecast errors, which is a normal distribution with mean 0 and variance $(1.69\mathrm{C})^2$ in New York state (32). Subscripts l_i and u_i indicate, respectively, lower and upper bounds of each of the three categories (i) as functions of x. For example, to calculate the probability of occurrence of SV equal to one, substituting into (eq. 1) yields the following expression:

$$\begin{aligned}P(\mathrm{SV}=1)=&\,P\left(\frac{7.2-T_f}{1.69}\leq z\leq\frac{11.6-T_f}{1.69}\right)P(16\leq y\leq 18)\\&+P\left(\frac{11.7-T_f}{1.69}\leq z\leq\frac{15.0-T_f}{1.69}\right)P(13\leq y\leq 15)\\&+P\left(\frac{15.1-T_f}{1.69}\leq z\leq\frac{26.6-T_f}{1.69}\right)P(10\leq y\leq 12)\end{aligned} \tag{2}$$

where T_f is forecast temperature (C) and z is the standard normal variable that represents the temperature errors (difference of observed and forecast). Probabilities for the other three severity values were computed in an analogous manner. Probability for an SV = 0 was calculated as the difference up to one of the sum of the four probabilities.

It would be most desirable to calculate daily probability values for each SV, and then to evaluate the incorporation of weather forecasts into BLITECAST. However, this requires a huge sequence of forecasts that are not available, because MOS temperature and dewpoint forecasts have been issued only since 1985; 1986–1988 forecasts were used to construct the model of Wilks and Shen (32), and we did not have 1989 and 1990 data sets. For this reason, RH duration and temperature forecasts were simulated stochastically.

The simulated forecasts were derived as follows: Bayes' theorem was applied to the beta distributions of relative humidity duration defined by the Wilks and Shen model (32), and probability functions of forecasts, conditional on the observed data, were calculated. Outcomes of daily relative humidity forecasts were generated randomly according to these functions. Similarly, daily temperature forecasts were generated consistent with the normal distribution of the temperature errors. In this way, for each observation of RH duration and mean temperature during wet period a limitless number of corresponding forecasts were generated. These forecasts represent those that could have been issued in advance of the observed relative humidity duration for that day.

The expression for the Bayes' theorem was adjusted to correct the difference in moisture period duration between specific locations (RH observed) and airport (RH forecast), since the airport conditions are, in general, warmer and drier than in a crop canopy. If $P(\text{obs}_j \mid \text{fcst}_i)$ denotes the probability of observing a number of hours (j) of relative humidity ≥90% from 0 to 23, given a particular forecast (i) for the next 23 h, and $P(\text{fcst}_i)$ represents the probability of each of the $i = 0, 1, ..., 23$ forecast durations, the usual expression for Bayes theorem is a function of $P(\text{fcst}_i)$, and is the following:

$$P(\text{fcst}_i \mid \text{obs}_j) = \frac{P(\text{obs}_j \mid \text{fcst}_i)\, P(\text{fcst}_i)}{\sum_{i=0}^{23} P(\text{obs}_j \mid \text{fcst}_i) P(\text{fcst}_i)} \quad (3)$$

Substituting

$$P(\text{fcst}_i) = \sum_j P(\text{fcst}_i \mid \text{obs}_j)\, P(\text{obs}_j) \quad (4)$$

into the numerator of (3), and

$$\sum_i P(\text{obs}_j \mid \text{fcst}_i)\, P(\text{fcst}_i) = P(\text{obs}_j) \quad (5)$$

into the denominator of (3) yields the expression

$$P(\text{fcst}_i \mid \text{obs}_j) = \frac{P(\text{obs}_j \mid \text{fcst}_i)[\sum_{j=0}^{23} P(\text{fcst}_i \mid \text{obs}_j) P(\text{obs}_j)]}{P(\text{obs}_j)} \quad (6)$$

Equation 6 is a function of $P(\text{obs}_j)$ and was solved iteratively. The effect of this adjustment is to allow stochastic simulation of sequences of forecasts consistent with both the statistical distribution of observed RH durations at field locations and the forecast accuracy characteristics (available only for the airport locations) specified by the distributions $P(\text{obj}_i \mid \text{fcst}_j)$.

Once the daily probability of each severity value was calculated, the expected (i.e., probability-weighted average) severity value was determined. BLITECAST is based on weather conditions for the previous 7 days; therefore, to incorporate weather forecasts into BLITECAST, the expected severity value for the 7th day was added to those observed values accumulated during the previous six days.

Differences in area under the disease progress curve (AUDPC) in the simulations were evaluated by Fisher's protected least significant difference test. These differences resulted from timing sprays according to BLITECAST with observed weather data and forecast weather and when perfect knowledge of relative humidity duration and temperature for the next 24 h was assumed. an estimate of the AUDPC with weather forecasts. The corresponding design was a randomized complete block, blocking on years. For BLITECAST with forecast weather we subsampled among years. The analysis was performed for weather favorable and moderately favorable for late blight (subtraction of 2 h from the daily relative humidity duration).

Verification of probability forecasts. Probability forecasts for each severity value were evaluated in a reliability diagram (19) (Fig. 1). Probability forecasts are reliable if the relative frequency of a specific severity value with assigned probability tends to be close to this probability. In a reliability diagram, observed relative frequencies are plotted against forecast probability values and compared with a perfect reliability line (where relative frequency is equal to forecast probability). Only points for which at least five forecasts occurred are plotted.

A total of 4,030 data values (13 yr × 5 outputs of stochastically generated forecast weather per year × 62 days of epidemic during the season) were used in the verification.

Maximum contribution of weather forecasts. Simulations were done to estimate the maximum benefit from weather forecasts by regarding future weather from the data set (1 or 2 days) to be a weather forecast of 100% accuracy. Fungicide applications were scheduled according to BLITECAST and the simulation forecast using this perfectly accurate knowledge of future weather. All the variables used for both disease forecasts (rainfall, mean temperature, hours of relative humidity ≥90%, and mean temperature during the high humidity period) were included in the perfect knowledge of future weather. When the disease forecast system scheduled an application, it was applied on the same day as the weather forecast became known. In the simulations, a spray was applied only if the minimum period between treatments (5–7 days for BLITECAST and 6 days for simulation forecast) had passed. Simulations were also done with sprays applied every 17, 13, 11, 9, 8, 7, 6 and 5 days, which give a total number of sprays per season of 4, 5, 6, 7, 8, 9, 10 and 12, respectively.

Average percentage of control per application was calculated as follows:

$$C = \frac{100(1 - \text{AUDPC}_t / \text{AUDPC}_u)}{N} \quad (7)$$

in which AUDPC_t is the mean area under disease progress curve (AUDPC) for a spray schedule, AUDPC_u is the mean AUDPC for the untreated, and N is the number of scheduled applications.

Differences in AUDPC and percentage of control among different spray schedules were evaluated in an ANOVA test, with years as a block factor.

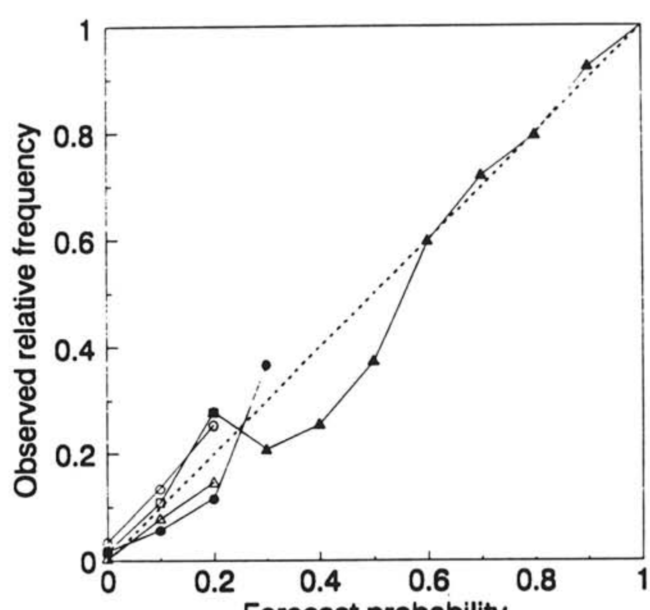

Fig. 1. Reliability diagram for the occurrence of daily severity value (SV) = 0 (▲); SV = 1 (○); SV = 2 (□); SV = 3 (△); and SV = 4 (●); diagonal dashed line indicates perfect reliability. SV refers to favorability of weather for late blight disease development as defined by Wallin, 1962 (31). Number of forecasts are given in Table 2.

RESULTS

Incorporation of weather forecasts into BLITECAST. Use of weather forecasts and perfect knowledge of future weather (duration of high relative humidity period and mean temperature) 1 day in advance, increased significantly ($P = 0.0001$) the average efficiency of fungicide use with BLITECAST when the unmodified weather data from Steuben County, New York (= favorable weather), were used. The number of scheduled fungicide applications was the same, while the average AUDPC significantly decreased compared to the use of BLITECAST without knowledge of future weather (Table 1). Moreover, the mean AUDPC significantly decreased as accuracy of the forecast weather increased (Table 1). That is, mean AUDPC for future weather (perfect forecast) was smaller than AUDPC for forecast weather (imperfect).

The simulation experiments demonstrated that the benefit from incorporating weather forecasts into disease forecasts may depend on weather. Disease suppression and number of fungicide applications resulting from BLITECAST use with forecast weather were the same as those for BLITECAST without weather forecasts, when weather conditions were moderately favorable for late blight. However, there was a significant reduction in the AUDPC when perfect knowledge of future weather was used (Table 1). The number of applications did not vary.

TABLE 1. Effect of incorporating weather forecasts into BLITECAST to control late blight using protectant fungicide in simulation experiments with 50 yr of weather data

Weather to time fungicides with BLITECAST[a]	Weather for late blight disease: Favorable AUDPC[c]	Favorable Fungicide applications[d]	Moderately favorable[b] AUDPC[c]	Moderately favorable[b] Fungicide applications[d]
Observed	4.01 a[e]	10.6 (±1.13)	3.43 a	8.0 (±1.50)
Future (perfect fcst)	3.58 c	10.6 (±1.15)	2.62 b	8.0 (±1.49)
Forecast[f]	3.79 b	10.8 (±1.08)	3.56 a	7.9 (±1.44)

[a] Future weather assumes perfect knowledge of relative humidity duration and its mean temperature 1 day in advance; forecast weather is incorporated as described in the text.
[b] Moderately favorable weather data were obtained by subtracting 2 h from daily relative humidity duration in favorable weather.
[c] Mean of area under disease progress curve in proportion-days.
[d] Mean (± standard deviation).
[e] Numbers within the column for each type of weather followed by the same letter are not significantly different at 5% level, as determined by Fisher's protected LSD test.
[f] Mean of 50 runs of stochastically generated daily weather forecasts for each of the 50 yr of observed weather data.

TABLE 2. Frequency distributions of forecast probabilities assigned to the occurrence of several severity values (SV)

Forecast probability values[a]	Number of occurrences[b] of SV = 0	SV = 1	SV = 2	SV = 3	SV = 4
0.0	0	57	116	547	1,509
0.1	0	479	1,298	2,552	2,039
0.2	18	3,494	2,616	931	462
0.3	519	0	0	0	19
0.4	1,278	0	0	0	1
0.5	1,017	0	0	0	0
0.6	549	0	0	0	0
0.7	329	0	0	0	0
0.8	206	0	0	0	0
0.9	79	0	0	0	0
1.0	35	0	0	0	0

[a] Values are center of classes; their corresponding upper limits are 0.049, 0.149 . . . 0.949, 1.0.
[b] Total number of forecasts used in the evaluation is 4,030 (13 yr × 5 outputs of stochastically generated weather forecast × 62 days of epidemic in the season).

Verification of probability forecasts. Comparison of the empirical lines for each severity value (SV) with the perfect reliability line indicated that predicted probabilities for SV occurrences were quite similar to the observed probabilities; thus, the similated forecasts were reasonable approximations of real forecasts (Fig. 1). For SV = 3 and SV = 4 events, forecast probabilities were slightly higher than the corresponding observed relative frequencies. This was also observed for low probability values in the case of SV = 0. An opposite tendency was observed for SV = 1 and SV = 2 events. Frequency distributions for these forecasts (Table 2) indicate that a very narrow range of low probability values were assigned to SV = 1, SV = 2, SV = 3, and SV = 4.

Maximum contribution of weather forecasts. Perfect knowledge of future weather 1 or 2 days in advance increased the average level of disease suppression achieved by a protectant fungicide scheduled for both disease forecasts in all weather conditions tested. When fungicide applications were scheduled according to BLITECAST, use of perfectly known future weather reduced significantly the average AUDPC, whereas the number of applications was the same (Table 3). However, BLITECAST performance on average was no better than fungicide sprays applied at regular intervals to control late blight (Fig. 2). For favorable weather conditions for disease development, fungicide applications scheduled with BLITECAST with or without perfect knowledge of future weather (1 or 2 days) did not call for fewer applications than did the conventional weekly schedule (nine sprays per season) (Fig. 2A). The contribution of each spray to disease suppression was significantly larger for a spray applied weekly than for one applied using BLITECAST schedules (Table 3).

For moderately and less favorable weather conditions for late blight, the average number of sprays recommended by BLITECAST with observed or perfect future weather was less

TABLE 3. Percentage of control per application of protectant fungicide achieved by BLITECAST when perfect knowledge of future weather is assumed, for 50 yr in three different weather conditions for late blight disease development

Weather	Spray schedule[a]	AUDPC[b]	No. of applications[c]	Percent control per application[d]
Favorable	BLITECAST	3.96 (±1.38) b[f]	10.6 (±1.13)	8.05 c[f]
	BLITECAST 1	3.54 (±1.31) c	10.6 (±1.11)	8.20 bc
	BLITECAST 2	3.48 (±1.31) c	10.5 (±1.12)	8.33 b
	Weekly	4.53 (±1.85) a	9 (±0)	9.10 a
	Untreated[e]	24.56 (±1.65)	0	
Mod. favorable[g]	BLITECAST	3.43 (±1.73) a	8.0 (±1.49)	10.91 b
	BLITECAST 1	2.62 (±1.48) b	8.0 (±1.46)	11.39 ab
	BLITECAST 2	2.45 (±1.31) b	7.9 (±1.45)	11.64 a
	Weekly	1.72 (±1.10) c	9 (±0)	10.24 c
	Untreated	21.06 (±2.28)	0	
Less favorable[g]	BLITECAST	3.98 (±2.58) a	4.7 (±1.70)	17.44 a
	BLITECAST 1	3.32 (±2.46) b	4.7 (±1.58)	18.12 a
	BLITECAST 2	3.07 (±2.50) b	4.7 (±1.58)	18.49 a
	Weekly	0.36 (±0.34) c	9 (±0)	10.87 b
	Untreated	14.73 (±3.30)	0	

[a] BLITECAST, BLITECAST 1, and BLITECAST 2 indicate that spray schedule was determined according to BLITECAST using, respectively, observed weather data, perfectly known future weather 1 day in advance, and 2 days in advance.
[b] Mean of area under disease progress curve in proportion-days (± standard deviation).
[c] Mean (± standard deviation).
[d] Percentage of control per application of protectant fungicide was calculated as described by equation (7).
[e] Untreated was not included in the ANOVA test.
[f] Numbers within the column for each type of weather followed by the same letter are not significantly different at 5% level, as determined by Fisher's protected LSD test.
[g] Moderately and less favorable weather data were obtained by subtracting 2 and 4 h, respectively, from daily relative humidity duration in favorable weather.

than the weekly schedule, but the greater number of sprays in the weekly schedule suppressed disease to a lower level (Fig. 2B, C). The percentage of control per application achieved by one spray in the BLITECAST treatment was significantly larger than that achieved by the conventional spray schedule (Table 3).

When perfect knowledge of future weather was incorporated into the simulation-based forecast to time fungicide applications, the AUDPC was smaller than it was when using observed weather, but more fungicide was used regardless of the weather conditions for late blight development (Fig. 2). Unlike BLITECAST, incorporation of perfect future weather into the simulation forecast resulted in disease suppression as good as or better than that achieved by fungicide applications at regular intervals. However, the number of sprays applied in favorable and moderately favorable weather for late blight was larger than for the weekly schedule.

DISCUSSION

The potential effect of incorporating weather forecasts into two existing potato late blight forecasts was evaluated. As expected, the effect was to increase the efficiency (reduction in AUDPC/fungicide application) in the use of the protectant fungicide. The main effect of chlorothalonil, the protectant fungicide used regularly to control late blight disease, is to inhibit the germination of either zoospores or sporangia of *Phytophthora infestans* (3). Therefore, the use of the weather forecasts make it possible to protect the plant before infections are initiated, when a protectant fungicide is effective.

It had been suggested previously that the failure of BLITECAST to time fungicide applications better than the use of fungicide at regular intervals was because of the use of past weather (11). When simulated forecasts of RH duration and mean temperature during this period were incorporated into BLITECAST to time fungicide applications, the effect was to reduce average AUDPC while applying the same average number of sprays (Table 1). These results indicate improved fungicide timing when weather forecasts are used. The reduction in AUDPC with forecast weather was less than that achieved with perfect future weather. These results only occurred when weather conditions were favorable for late blight disease.

The maximum contribution that might be expected when future weather is incorporated into BLITECAST or the simulation forecast was investigated because it provided a measure of the potential improvement that more accurate weather forecasts might achieve. When all weather variables needed to implement BLITECAST were known perfectly for 1 or 2 days into the future, the effect was to reduce the mean AUDPC without changing the average number of fungicide applications (Fig. 2, Table 3). The reduction in the AUDPC was larger when conditions were moderately favorable for late blight disease. Analysis of spray dates (data not presented) indicated that the major effect of using perfect knowledge of future weather with BLITECAST was to cause some applications to be applied a day or two earlier than they otherwise would have been. When perfect knowledge of future weather was used with the simulation-based forecast (13), the AUDPC was reduced, but the number of scheduled fungicide applications was increased (Fig. 2). However, the reliability of these results is uncertain because the simulation forecast was constructed from the same model that we used here to evaluate its response.

BLITECAST with observed or future weather did not perform better, on average, than spray applications at regular intervals. Results show that the maximum contribution of perfect forecast weather did not make BLITECAST perform better when compared to fungicide applications at fixed intervals. With the favorable weather data set, BLITECAST used with perfect knowledge of future weather scheduled, on average, more fungicide applications than did the weekly schedule. When weather was less favorable, BLITECAST used with perfect knowledge of future weather recommended fewer fungicide applications, but AUDPC was generally larger than that resulting from applications at regular intervals (Fig. 2, Table 3). Our results for BLITECAST without knowledge of future weather support previous studies (13), which indicated that BLITECAST-scheduled fungicide applications, on average, did not suppress late blight more efficiently (i.e., same reduction in AUDPC with less fungicide,

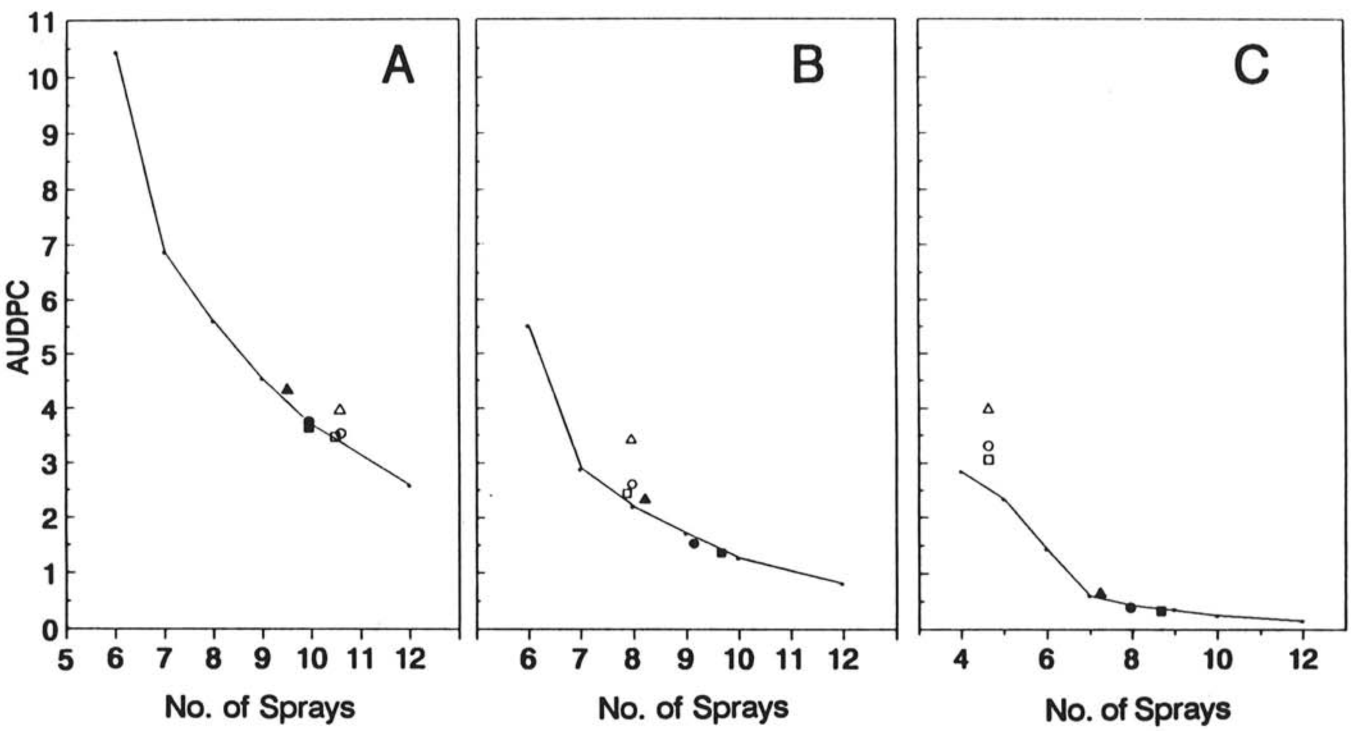

Fig. 2. Effect of incorporating perfect knowledge of future weather into potato late blight disease forecasts on the average of AUDPC and number of applications. Results are from 50 yr of **A,** favorable weather, **B,** moderately favorable, and **C,** less favorable conditions for late blight development. Protectant fungicide schedule was timed according to BLITECAST (△) and simulation-based forecast (13) (▲), with future weather known 1 day (○ for BLITECAST and ● for simulation forecast) or 2 days (□ for BLITECAST and ■ for simulation forecast) in advance. Regular sprays (●) were applied every 11, 9, 8, 7, 6, and 5 days (equivalent to 6, 7, 8, 9, 10, and 12 sprays per season).

or greater reduction in AUDPC with the same amount of fungicide) than did the conventional practice of weekly fungicide applications (Fig. 2, Table 3).

Percentage of control per application was calculated to evaluate the average contribution to disease suppression achieved by each fungicide application when BLITECAST was used to time fungicide sprays with observed and perfect forecast weather. The contribution from each spray increased as weather for late blight development became less favorable, and this increase was larger for BLITECAST-scheduled applications than for weekly sprays. This result indicates the benefit of using BLITECAST to time applications for locations where weather is sporadically favorable for late blight disease (midwest United States), and a lack of benefit in locations where weather is so favorable that disease is always a threat (i.e., northeast United States).

The probabilistic model of the conditional distributions of relative humidity duration on the MOS forecast values, and the associated temperature forecasts (32), was constructed in a way useful to calculate probability values of plant disease indexes involving relative humidity duration and its mean temperature. In this sense, the probablilistic model can be used with any disease forecast system employing those parameters. When applied to BLITECAST, the verification of probability forecasts assigned to the occurrence of severity values indicated that these probability forecasts were reliable (Fig. 1). This evaluation also represented an indirect assessment of the method described to simulate stochastically predictions of periods of daily relative humidity $\geq$90% and their mean temperatures. The method presented here to incorporate weather forecasts, i.e., the use of expected severity values, assumes that each disease index value represents a linear increase in the amount of disease. This assumption may not be valid in other disease forecast systems, and, to this extent, this aspect of the method is limited.

The results of this study indicated a positive contribution of weather forecasts to the efficacy of disease forecasts, but the contribution was smaller than we had hoped to discover. It might be that inaccuracies or simplifications in the models limited our ability to detect improvements from weather forecasts. For example, changes in fungicide formulation might improve the tenacity of fungicide, and this might enable larger contribution of weather forecasts. Unfortunately, changes in fungicide formulation appear not to make a large difference because comparisons between model predictions and field tests using recent fungicide formulations indicate that the disease models still accurately describe the effect of fungicide (26). Another possible reason for the limited positive benefit of weather forecasts may be the nature of the decision rules in the two disease forecasts employed. Evaluation of other decision rules seems to be a logical next step in the continuing effort to enhance the utility of disease forecasts.

LITERATURE CITED

1. Beaumont, A. 1947. The dependence on the weather of the dates of outbreak of potato late blight epidemics. Trans. Br. Mycol. Soc. 31:45-53.
2. Bourke, P. M. A. 1970. Use of weather information in the prediction of plant disease epiphytotics. Annu. Rev. Phytopathol. 12:345-370.
3. Bruck, R. I., Fry, W. E., Apple, A. E., and Mundt, C. C. 1981. Effect of protectant fungicides on the developmental stages of *Phytophthora infestans* in potato foliage. Phytopathology 71:164-166.
4. Bruhn, J. A., and Fry, W. E. 1981. Analysis of potato late blight epidemiology by simulation modeling. Phytopathology 71:612-616.
5. Bruhn, J. A., and Fry, W. E. 1982. A statistical model of fungicide deposition on potato foliage. Phytopathology 72:1301-1305.
6. Bruhn, J. A., and Fry, W. E. 1982. A mathematical model of the spatial and temporal dynamics of chlorothalonil residues on potato foliage. Phytopathology 72:1306-1312.
7. Carter, G. M., Dallavalle, J. P., and Glahn, H. R. 1989. Statistical forecasts based on the National Meteorological Center's numerical weather prediction system. Wea. Forecasting 4:401-412.
8. Cook, H. T. 1949. Forecasting late blight epiphytotics of potatoes and tomatoes. J. Agric. Res. 78:545-563.
9. Doster, M. A., Milgroom, M. G., and Fry, W. E. 1990. Quantification of factors influencing potato late blight suppression and selection for metalaxyl resistance in *Phytophthora infestans*: A simulation approach. Phypathology 80:1190-1198.
10. Doster, M. A., Sweigard, J. A., and Fry, W. E. 1989. The influence of host resistance and climate on the initial appearance of foliar late blight of potato from infected seed tubers. Am. Potato J. 66:227-233.
11. Fohner, G. R., Fry, W. E., and White, G. B. 1984. Computer simulation raises question about timing protectant fungicide application frequency according to a potato late blight forecast. Phytopathology 74:1145-1147.
12. Fry, W. E. 1982. Principles of Plant Disease Management. Academic Press, New York. 378 pp.
13. Fry, W. E., Apple, A. E., and Bruhn, J. A. 1983. Evaluation of potato late blight forecasts modified to incorporate host resistance and fungicide weathering. Phytopathology 73:1054-1059.
14. Fry, W. E., and Fohner, G. R. 1985. Construction of predictive models: I. Forecasting disease development. Pages 161-178 in: Advances in Plant Pathology. Vol. 3. Mathematical Modelling of Crop Disease. C. A. Gilligan, ed. Academic Press, New York.
15. Glahn, H. R., and Lowry, D. A. 1972. The use of model output statistics (MOS) in objective weather forecasting. J. Appl. Meteorol. 11:1203-1211.
16. Grainger, J. 1950. Forecasting outbreaks of potato late blight in West Scotland. Trans. Br. Mycol. Soc. 33:82-91.
17. Halseth, D. E., Sieczka, J. B., Tingey, W. M., and Zitter, T. A. 1987. Cornell Recommendations for Commercial Potato Production Cornell Extension Service, Ithaca, NY. 16 pp.
18. Hooker, W. I., ed. 1981. Compendium of Potato Diseases. American Phytopathological Society, St. Paul, MN.
19. Hsu, W.-R., and Murphy, A. H. 1986. The attributes diagram. A geometrical framework for assessing the quality of probability forecasts. Int. J. Forecasting 2:285-293.
20. Hyre, R. A. 1954. Progress in forecasting late blight of potato and tomato. Plant Dis. Rep. 38:245-253.
21. Hyre, R. A., and Horsfall, J. G. 1951. Forecasting potato late blight in Connecticut. Plant Dis. Rep. 35:423-431.
22. Krause, R. A., and Massie, L. B. 1975. Predictive systems: Modern approaches to disease control. Annu. Rev. Phytopathol. 13:31-47.
23. Krause, R. A., Massie, L. B., and Hyre, R. A. 1975. BLITECAST: A computerized forecast of potato late blight. Plant Dis. Rep. 59:95-98.
24. Large, E. C. 1953. Potato blight forecasting investigation in England and Wales. Plant Pathol. 2(1):1-15.
25. Milgroom, M. G., and Fry, W. E. 1988. A model for the effects of metalaxyl on potato late blight epidemics. Phytopathology 78:559-565.
26. Shtienberg, D. S., Doster, M. A., Pelletier, J. R., and Fry, W. E. 1989. Use of simulation models to develop a low-risk strategy to suppress early and late blight in potato foliage. Phytopathology 79:59-595.
27. Shtienberg, D., and Fry, W. E. 1990. Quantitative analysis of host resistance, fungicide, and weather effects on potato early and late blight using computer simulation models. Am. Potato J. 67:277-286.
28. Shtienberg, D. S., and Fry, W. E. 1990. Field and computer simulation evaluation of spray-scheduling methods for control of early and late blight of potato. Phytopathology 80:772-777.
29. Vincelli, P. C., and Lorbeer, J. W. 1988. Relation of precipitation probability to infection potential of *Botrytis squamosa* on onion. Phytopathology 78:1078-1082.
30. Vincelli, P. C., and Lorbeer, J. W. 1989. BLIGHT-ALERT: A weather-based predictive system for timing fungicide applications on onion before infection periods of *Botrytis squamosa*. Phytopathology 79:493-498.
31. Wallin, J. R. 1962. Summary of recent progress in predicting late blight epidemics in the United States and Canada. Am. Potato J. 39: 306-312.
32. Wilks, D. S., and Shen, K. W. 1991. Threshold relative humidity duration forecasts for plant disease prediction. J. Appl. Meteorol. 30:463-477.